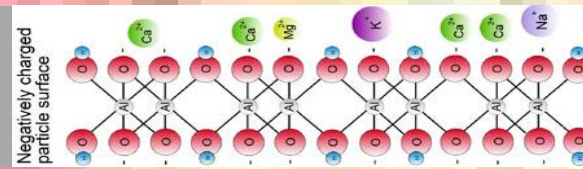


An Uncertainty Analysis for Predicting CEC and salinity Using gamma-ray and EM data

Jingyi Huang, Thomas Bishop,
John Triantafyllis

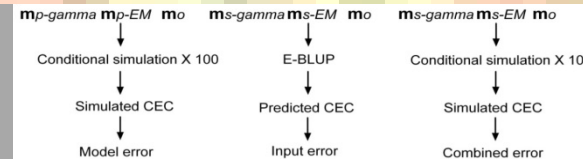
Problem
Definition?



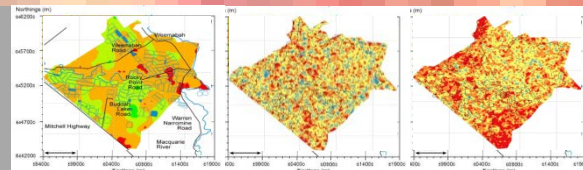
Digital soil mapping;
ancillary data



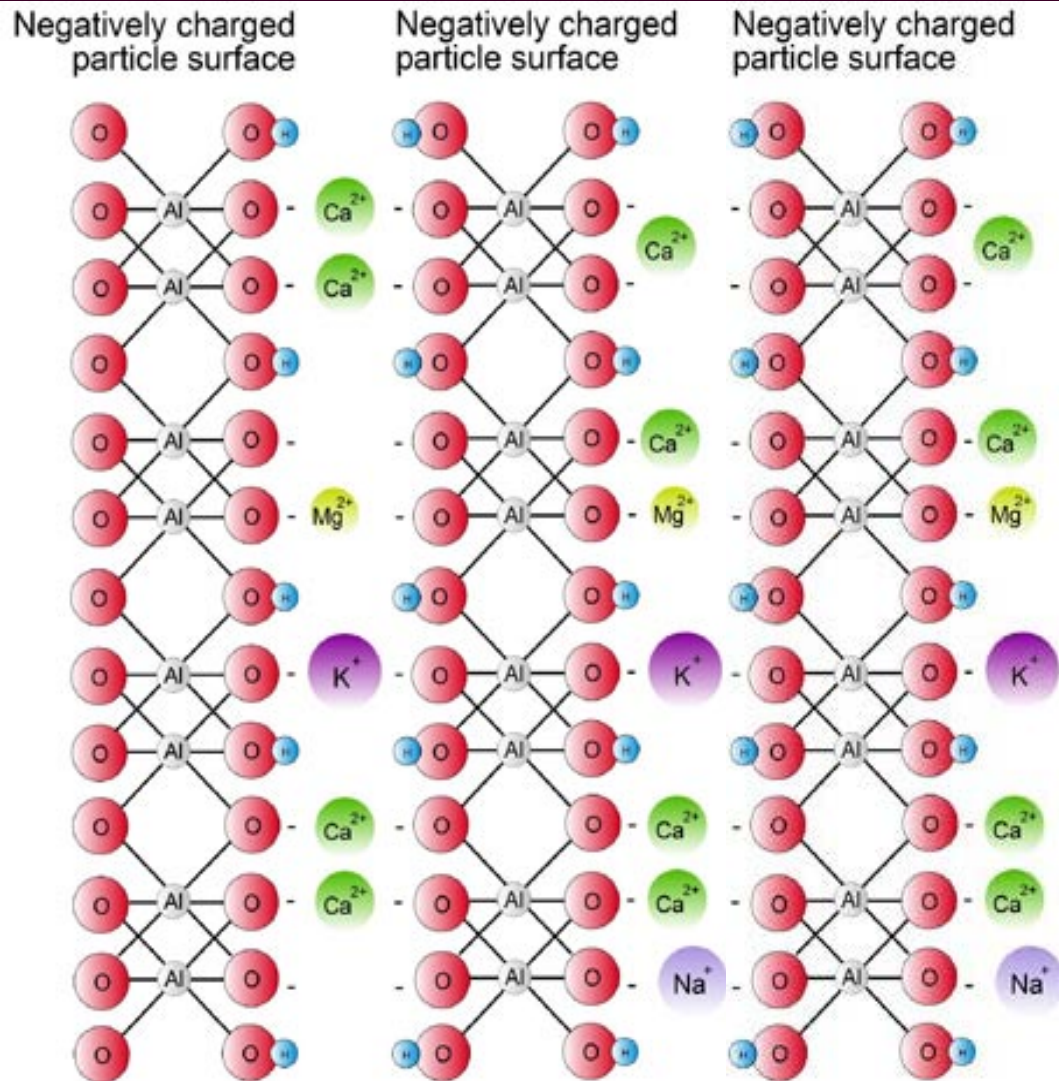
Digital soil mapping;
modelling and errors



Results, Discussion &
Conclusions



Introduction



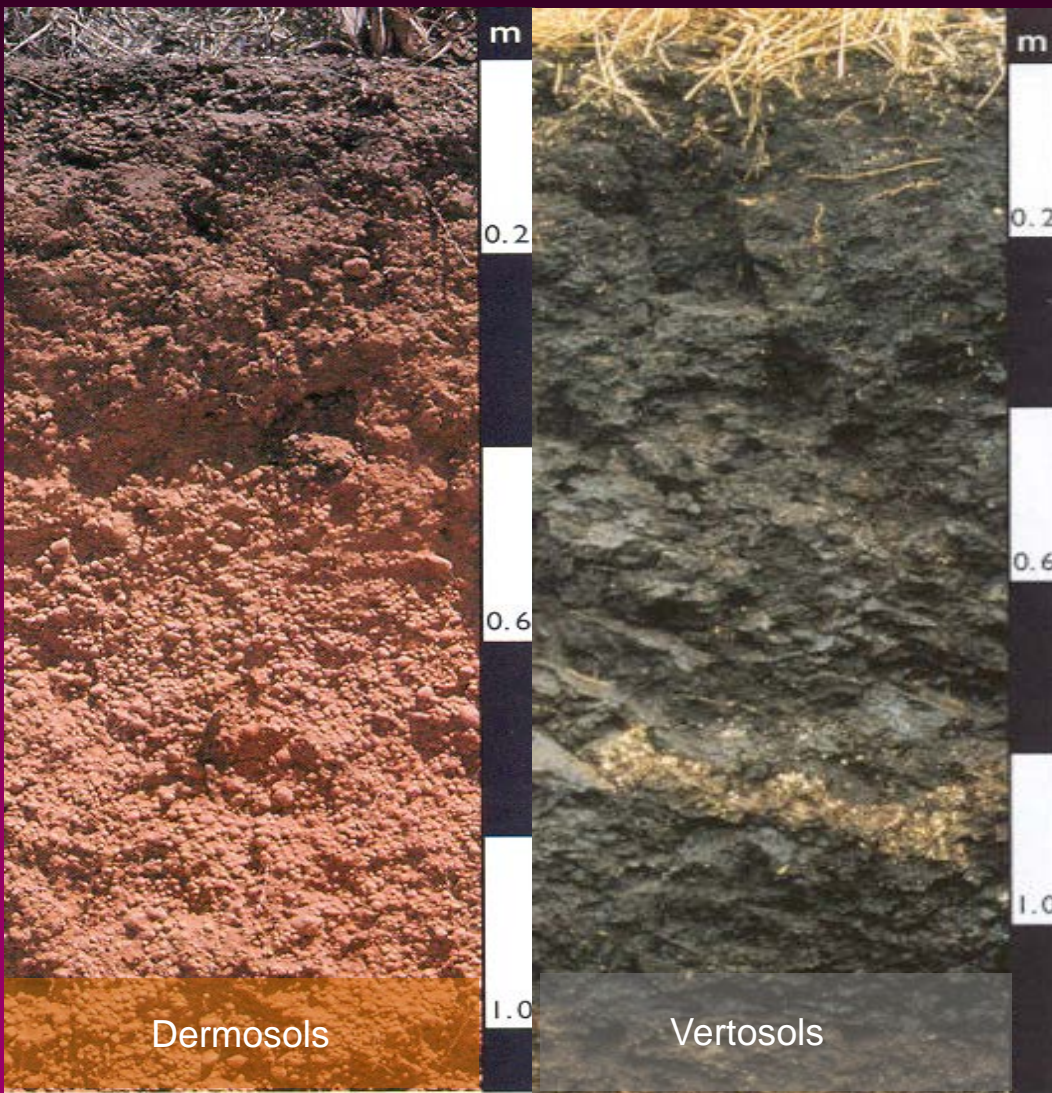
Cation exchange capacity

CEC is the total sum of exchangeable cations that soil can adsorb at a specific pH

It is widely used for agricultural assessment because CEC is a measure of fertility indicator of structural stability/resilience.

The latter is because CEC is capable of enhancing development of shrinkage cracks.



Introduction



CEC and shrink swell

In this regard, critical limits can be used in terms of shrink-swell properties.

Specifically, shrink swell potential

(cmol(+)/kg)	
	< 10
	< 20
	< 30
	>= 30

Very poor

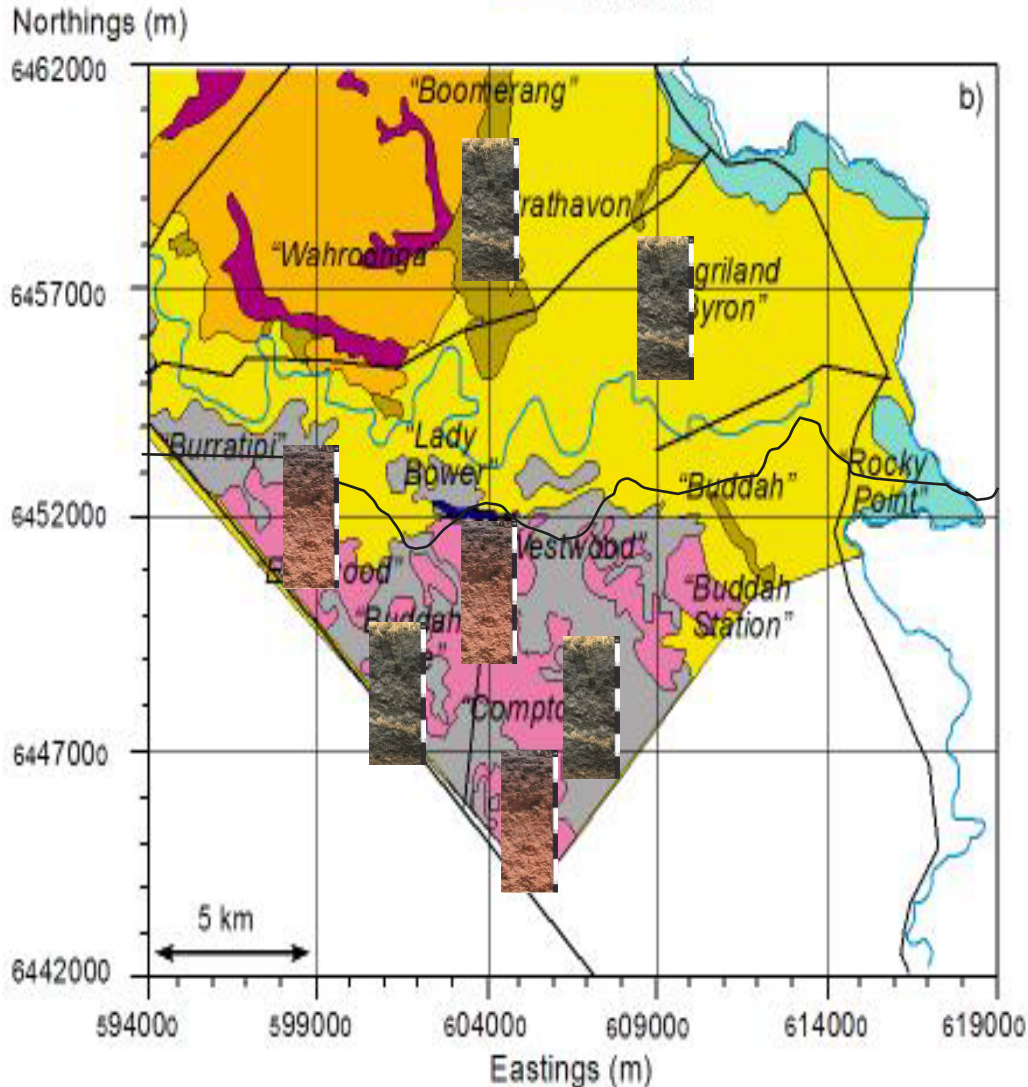
Poor

Moderate

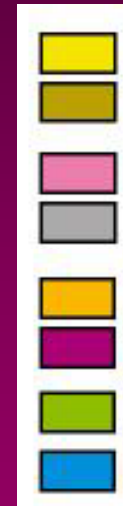
Good

CEC is time consuming because analysis requires determination of cations through a leaching process (Holmgren et al., 1977).

Problem definition



Pedoderms (McKenzie, 1992)



Trangie Cowl

Dermosols

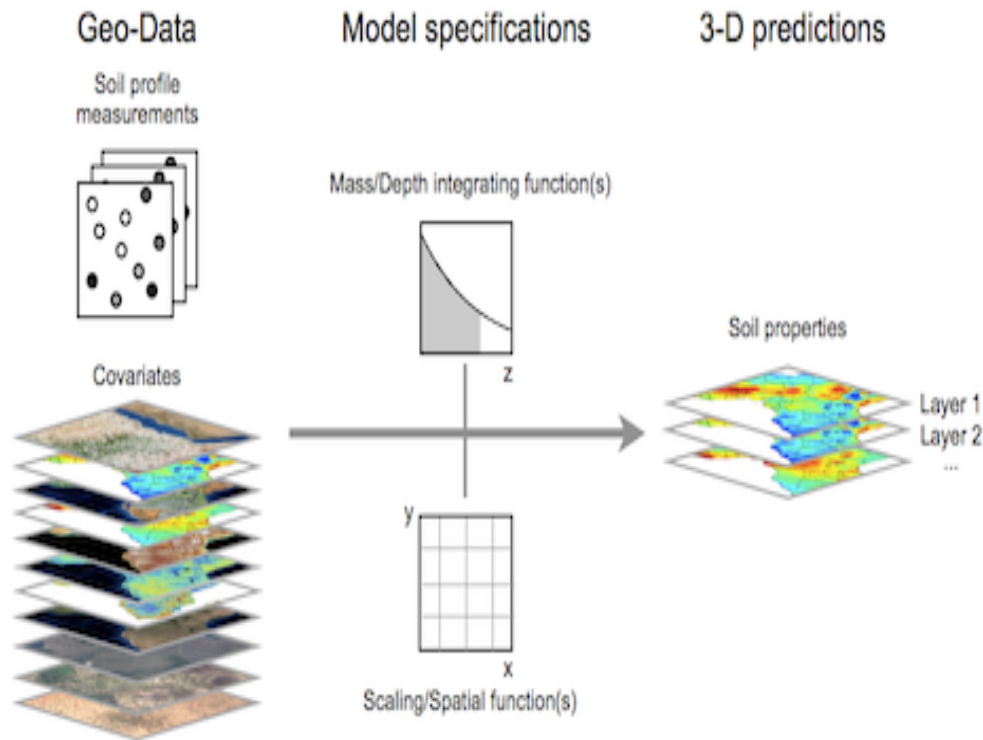
Old Alluvium Meander Plain

Old Alluvium Back Plain
Vertosols

Contemporary Macquarie

Aims and objectives

Digital soil mapping workflow



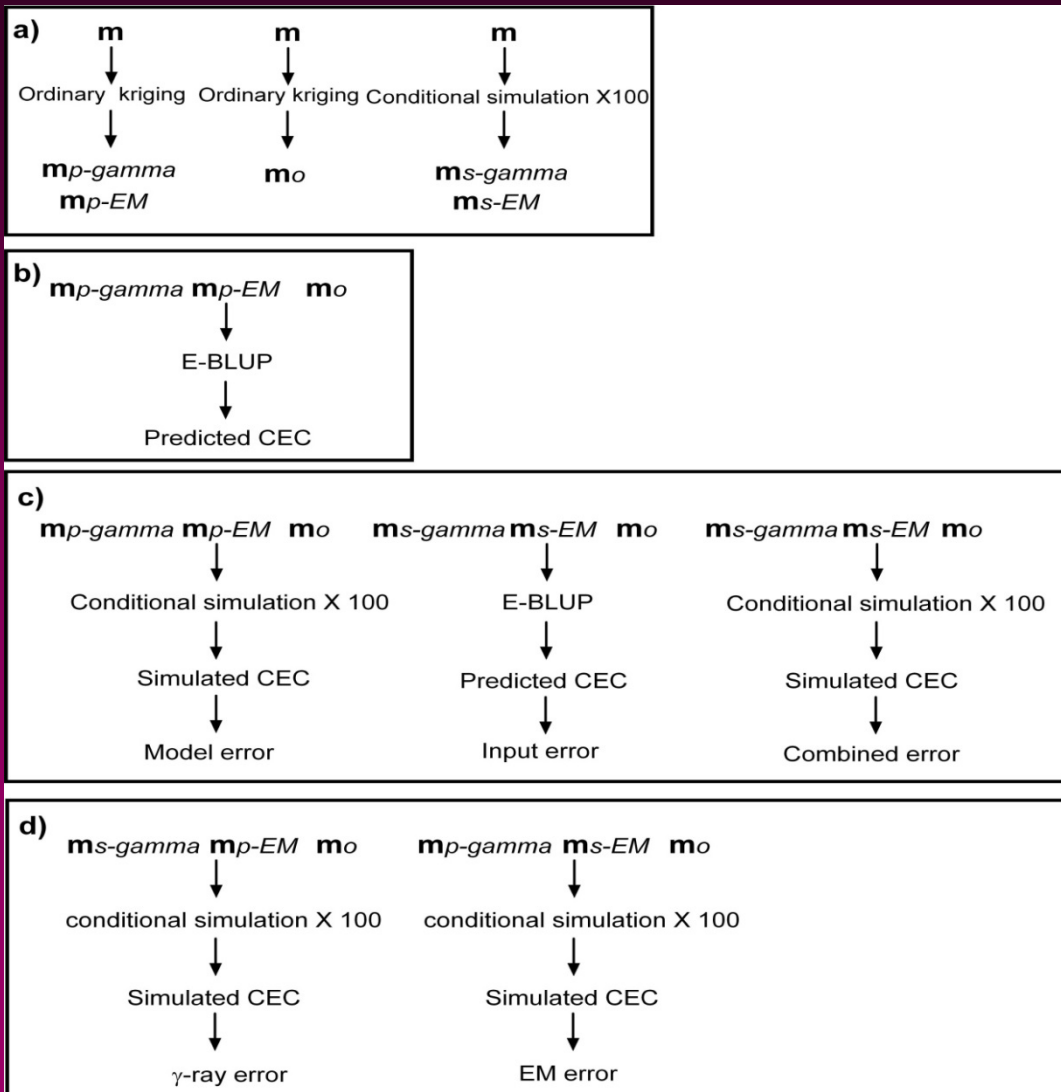
Use of DSM and error budgeting

Develop a DSM of topsoil (0-0.3 m) CEC using ancillary data, linear mixed model (LMM), and restricted maximum likelihood (REML).

Use an error budget procedure to quantify the relative contributions made by model, input (for both γ -ray and EC_a), and individual covariate error (ancillary data) when combining to map topsoil (0-0.3 m) CEC.

To understand distribution of different sources of errors

Materials and Methods: Modelling



Use of DSM and error budgeting

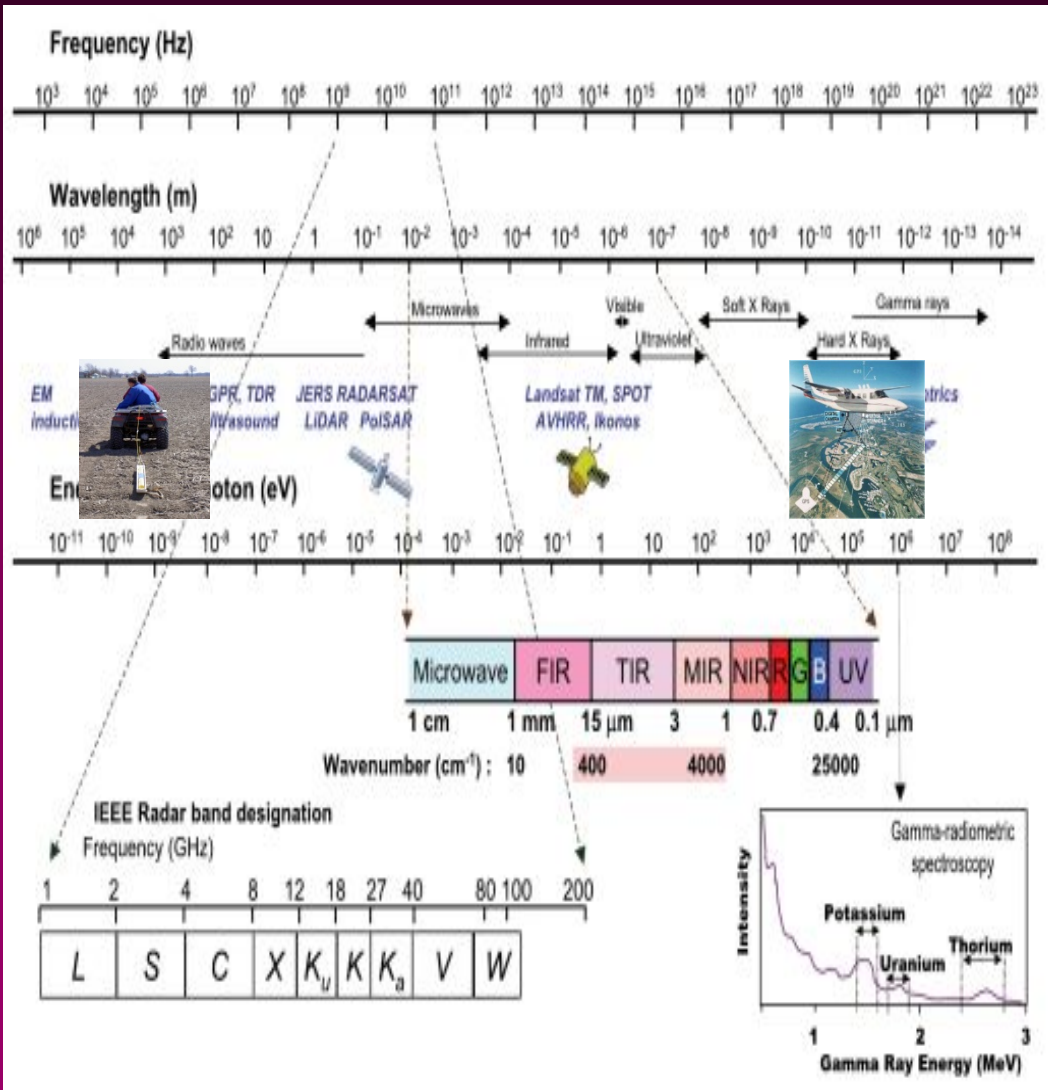
We use

- i) empirical best linear unbiased prediction (E-BLUP),
- ii) conditional simulation to produce numerous realizations of the data and their underlying errors, with
- iii) Linear mixed models (LMM)

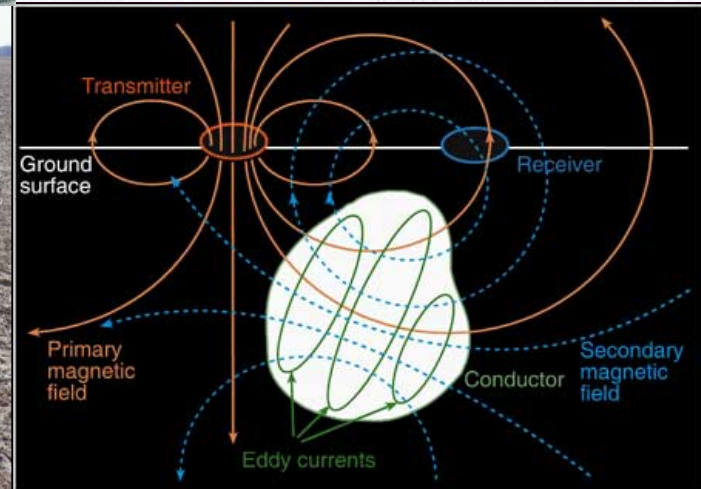
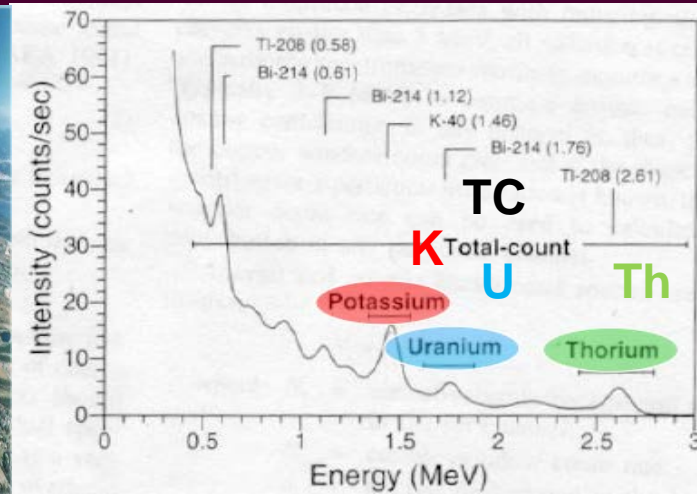
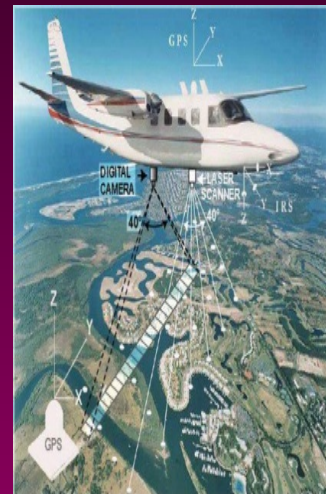
$$\mathbf{y} = \mathbf{X}\boldsymbol{\tau} + \mathbf{Z}\mathbf{u} + \boldsymbol{\varepsilon}$$

estimated by residual maximum likelihood (REML) to create the prediction models.

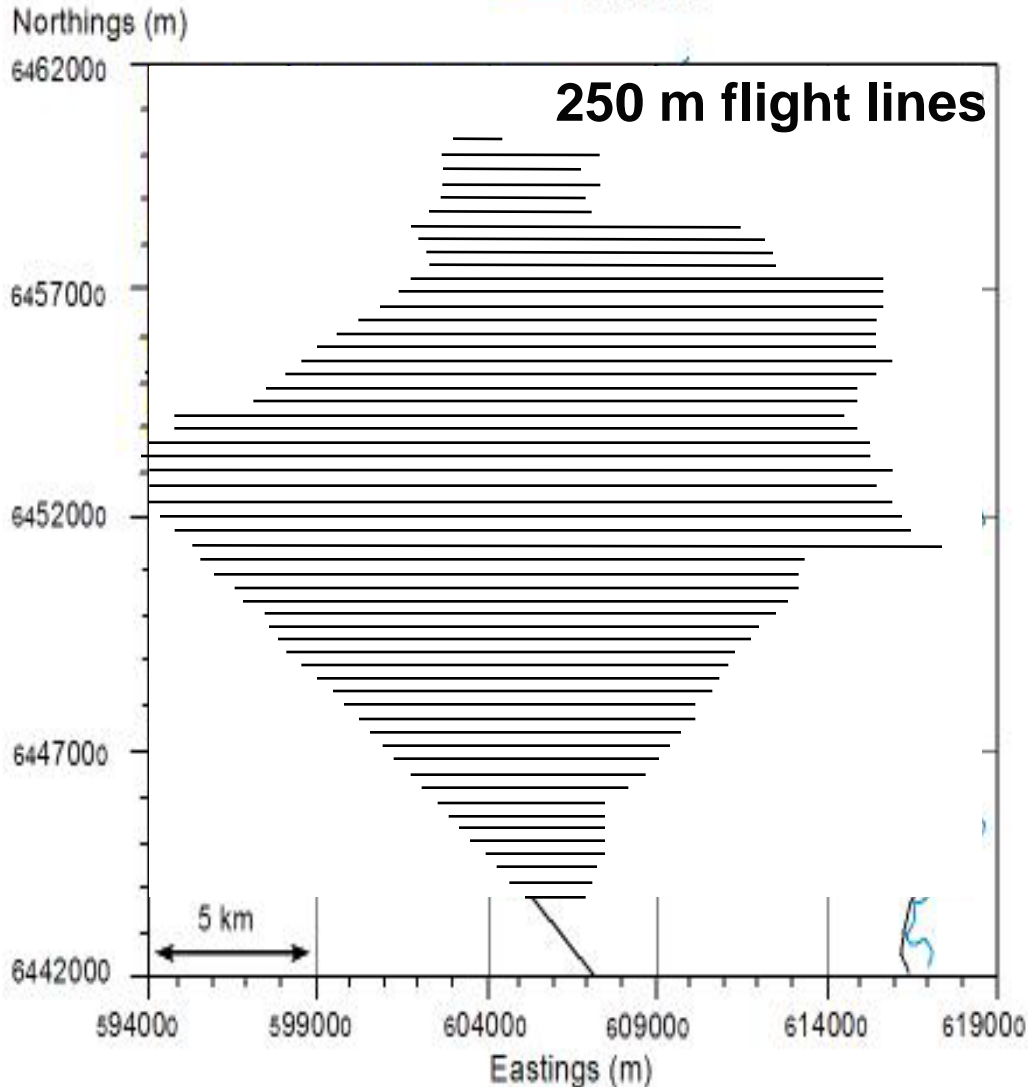
Materials and Methods



What covariates are commonly used?



Materials and Methods: Ancillary data

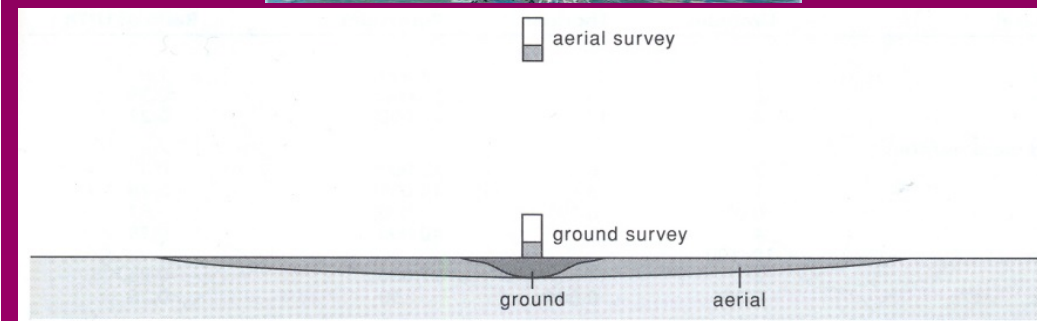


Airborne gamma-ray spectrometry

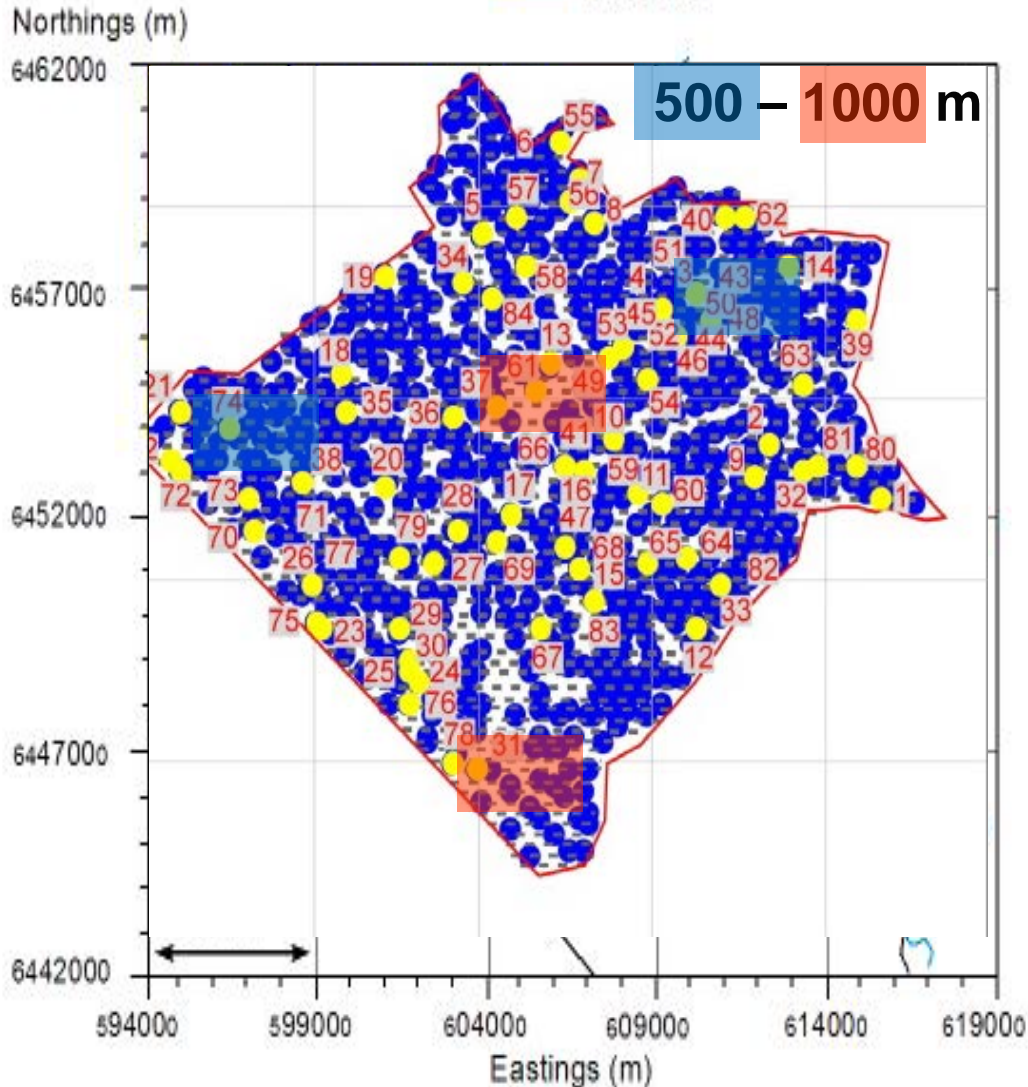
0

0.4

K,
U,
Th, and
TC



Materials and Methods: Ancillary data



Proximal EM

0

0.75

EM38h

1.50

EM38v



7 m

EM34-10

15 m

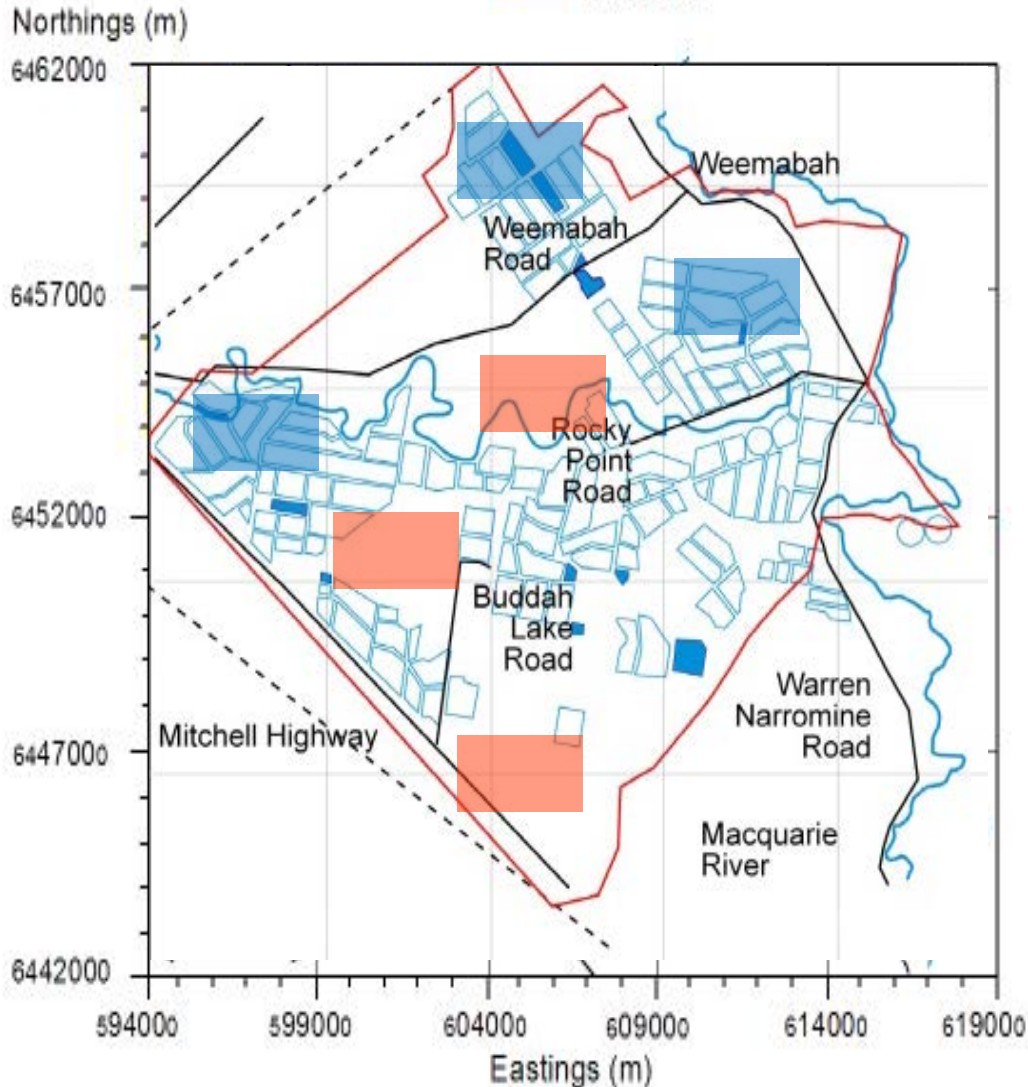
EM34-20

30 m

EM34-40



Materials and Methods



Study area

Trangie

Lower Macquarie valley

Central western New South Wales

Semi-arid

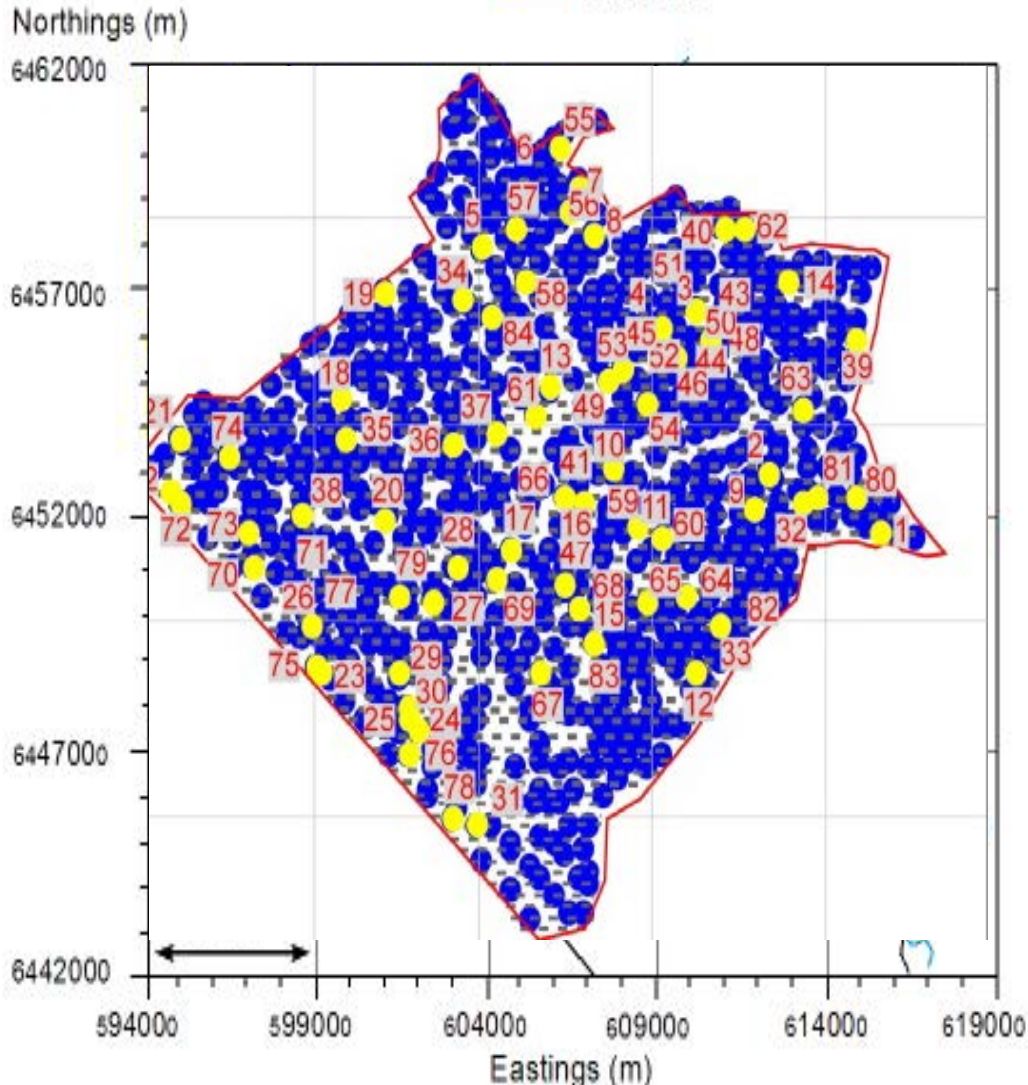
Rainfall - 560 mm/year

Hot summer ($>35\text{ }^{\circ}\text{C}$)

Land-use includes

grazing for sheep and cattle,
dryland wheat farming, and
irrigated cotton production

Materials and Methods: Soil data



Soil sampling and laboratory analysis

0 **Topsoil**

0.30 **CEC**

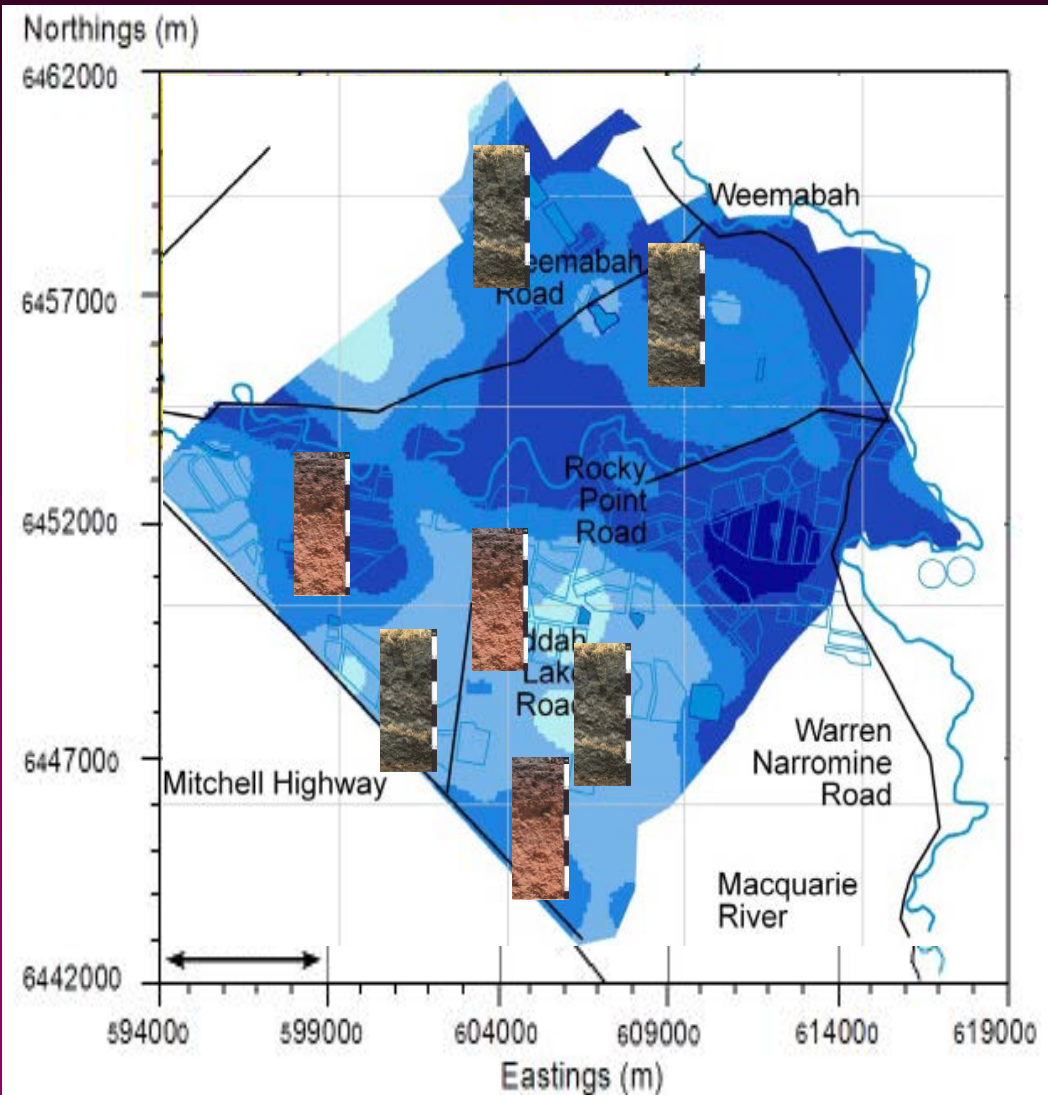


Soil - sampling based on Response Surface Sampling Design (RSSD) using EM34 (Triantafilis and Lesch, 2005)



CEC - Tucker's (1974) using leaching (Holmgren et al., 1977) because Vertosols alkaline with solid-carbonates (Loveday et al., 1972).

Results and Discussion: Ancillary data



Gamma-ray spectrometry

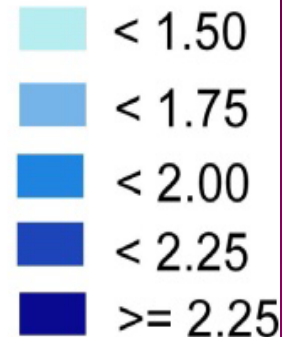
0

Topsoil

0.35

Uranium

(ppm)

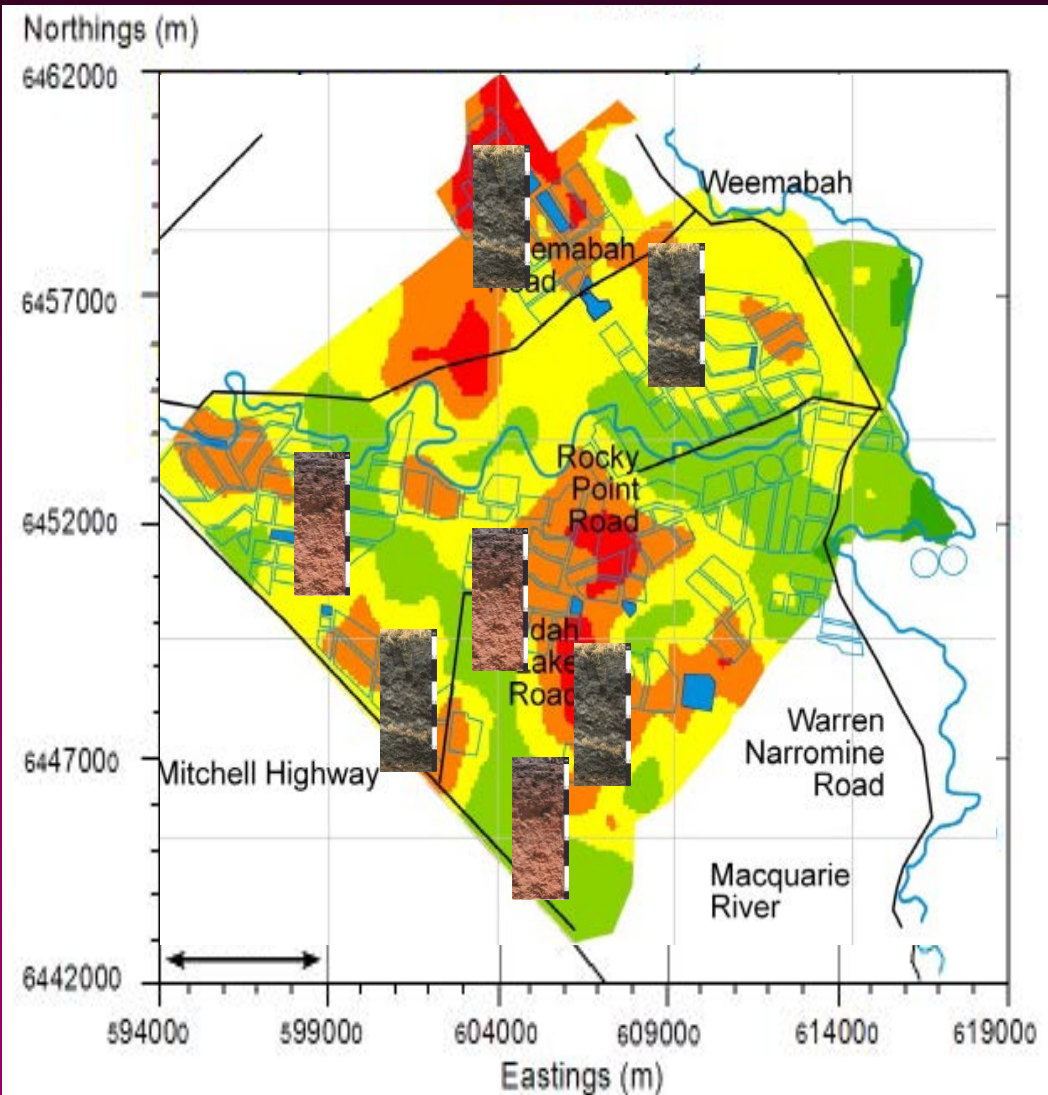


Dermosols

Old Alluvium Meander Plain

Old Alluvium Back Plain
Vertosols

Results and Discussion: Ancillary data



ECa

0

Topsoil

0.75

EM38h



Dermosols

Old Alluvium Meander Plain



Old Alluvium Back Plain

Vertosols

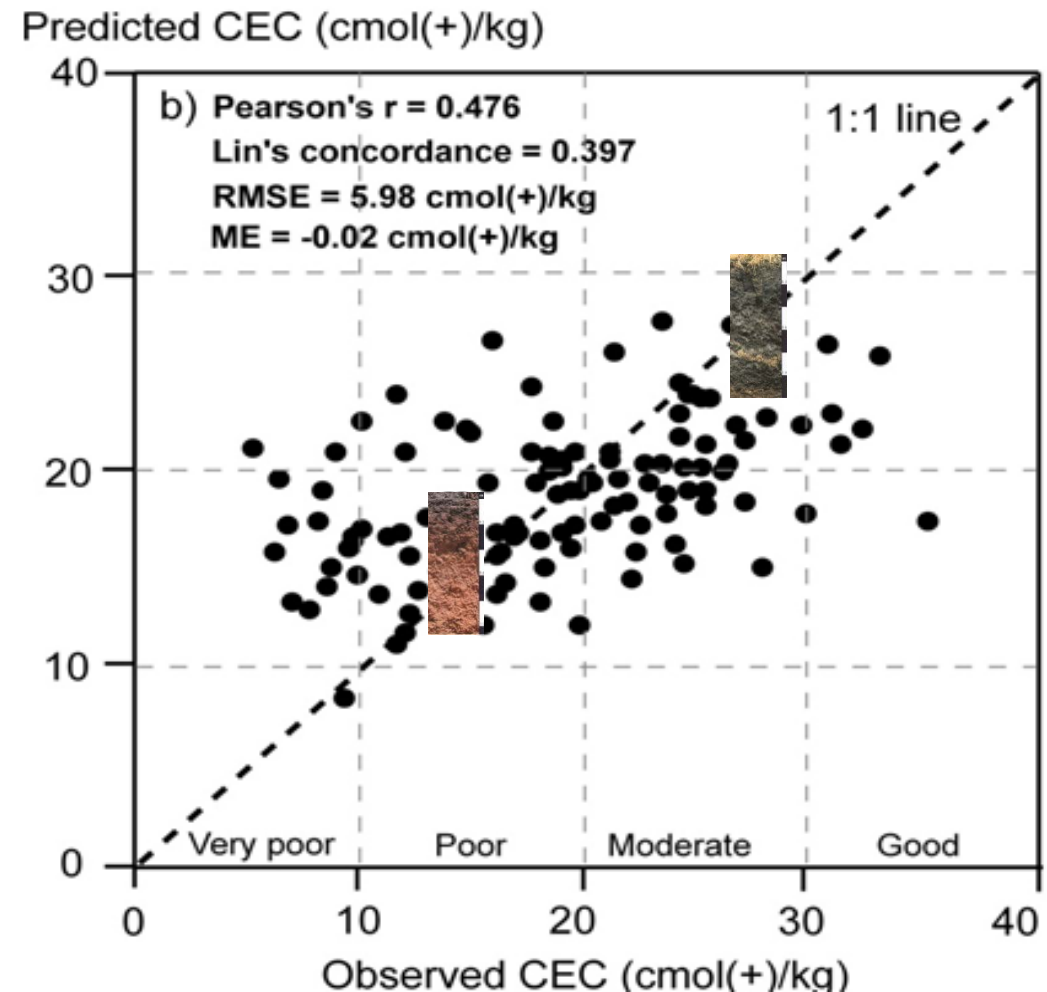
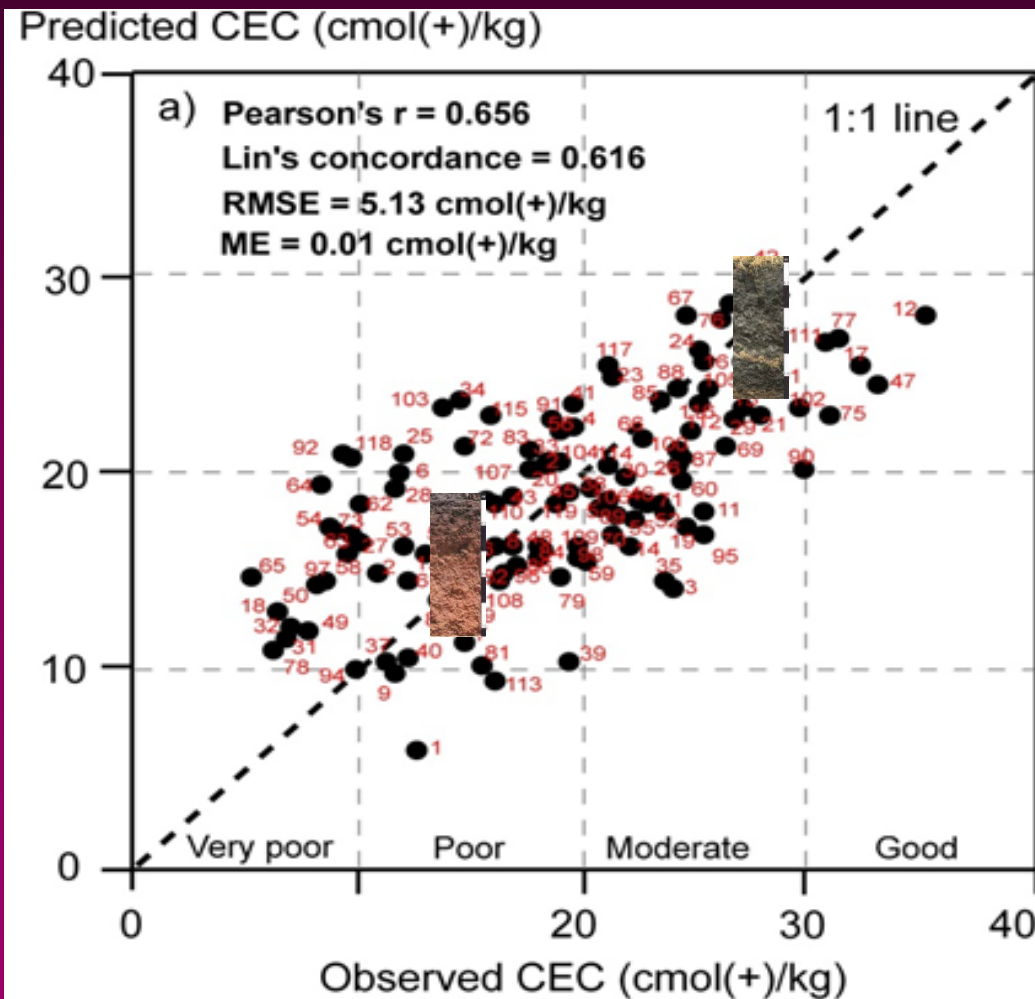
Results and Discussion

LMM models - fixed effect components

Spherical model	Estimates	Standard Error	Prob > t	Exponential model	Estimates	Standard Error	Prob > t
intercept	1.690	5.948	0.777	intercept	1.975	6.004	0.743
U	-11.434	3.531	0.002	U	-11.477	3.517	0.001
Th	3.893	0.969	<0.001	Th	3.920	0.973	<0.001
em34_10	0.285	0.047	< 0.001	em34_10	0.283	0.047	<0.001
em34_20	-0.122	0.042	0.004	em34_20	-0.124	0.042	0.003

Results and Discussion: Accuracy

Input



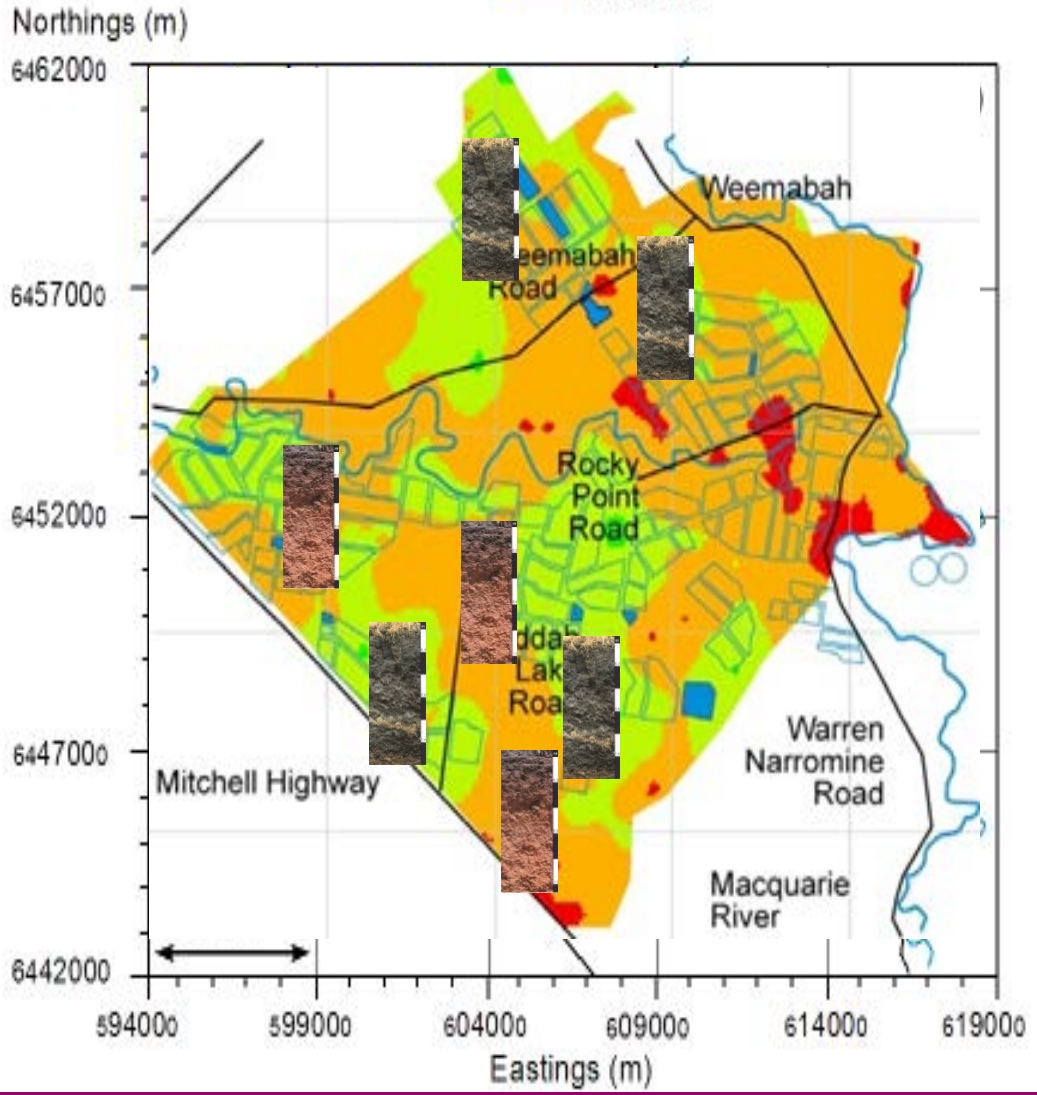
Results and Discussion: Visualisation

What do all these numbers mean?



Jasper Johns 0 - 9 1961 Oil paint on canvas

Results and Discussion: Prediction



Cation Exchange Capacity


CEC

(cmol(+)/kg)

 < 10

 < 20

 < 30

 ≥ 30

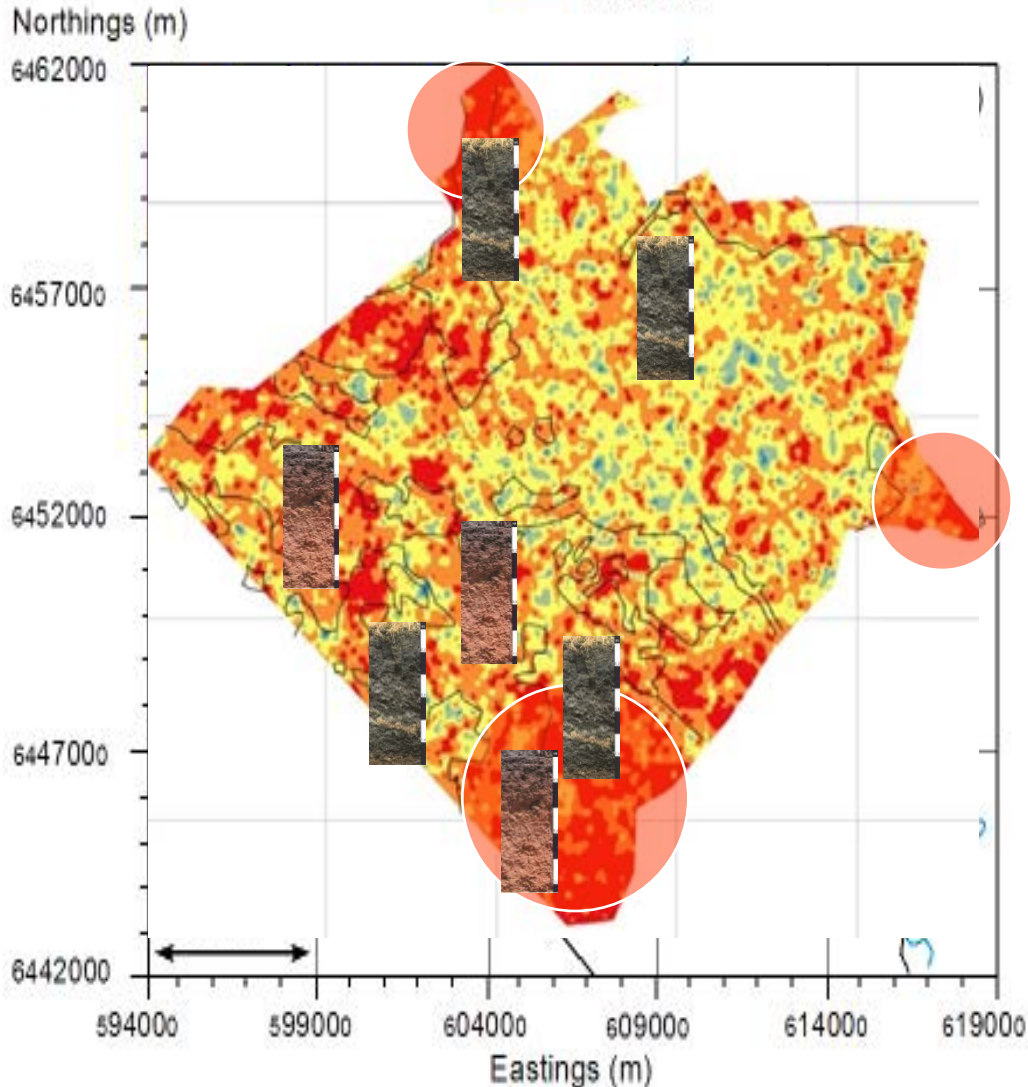


Dermosols

Old Alluvium Meander Plain

Old Alluvium Back Plain
Vertosols

Results and Discussion: Error



Model

Influenced by;
i) edge effects, and
ii) Pedoderm boundaries

SD

(cmol(+)/kg)

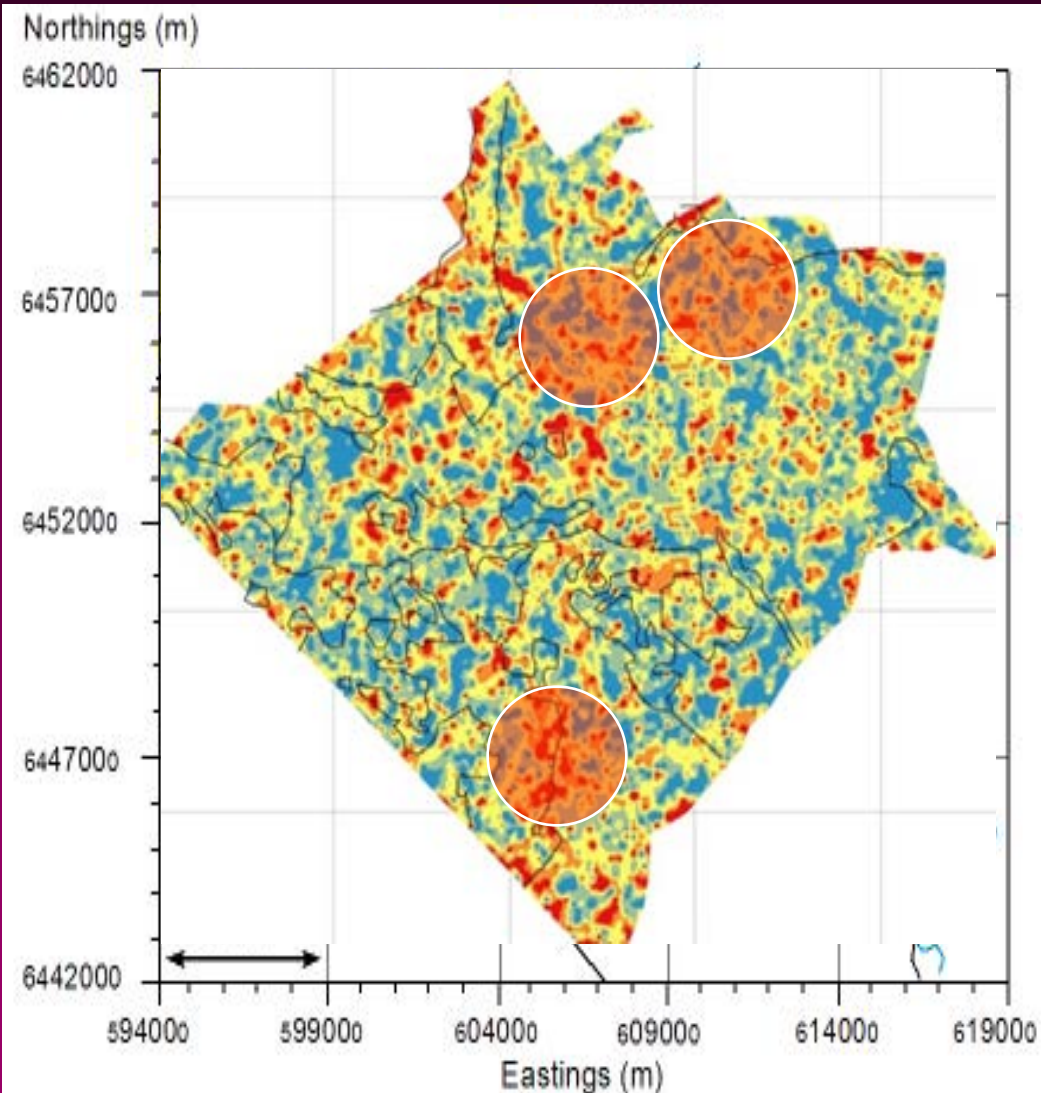


Derosols

Old Alluvium Meander Plain

Old Alluvium Back Plain
Vertosols

Results and Discussion: Error



Input

- Influenced by;
- Pedoderm boundaries,
 - Land-use management effect

SD



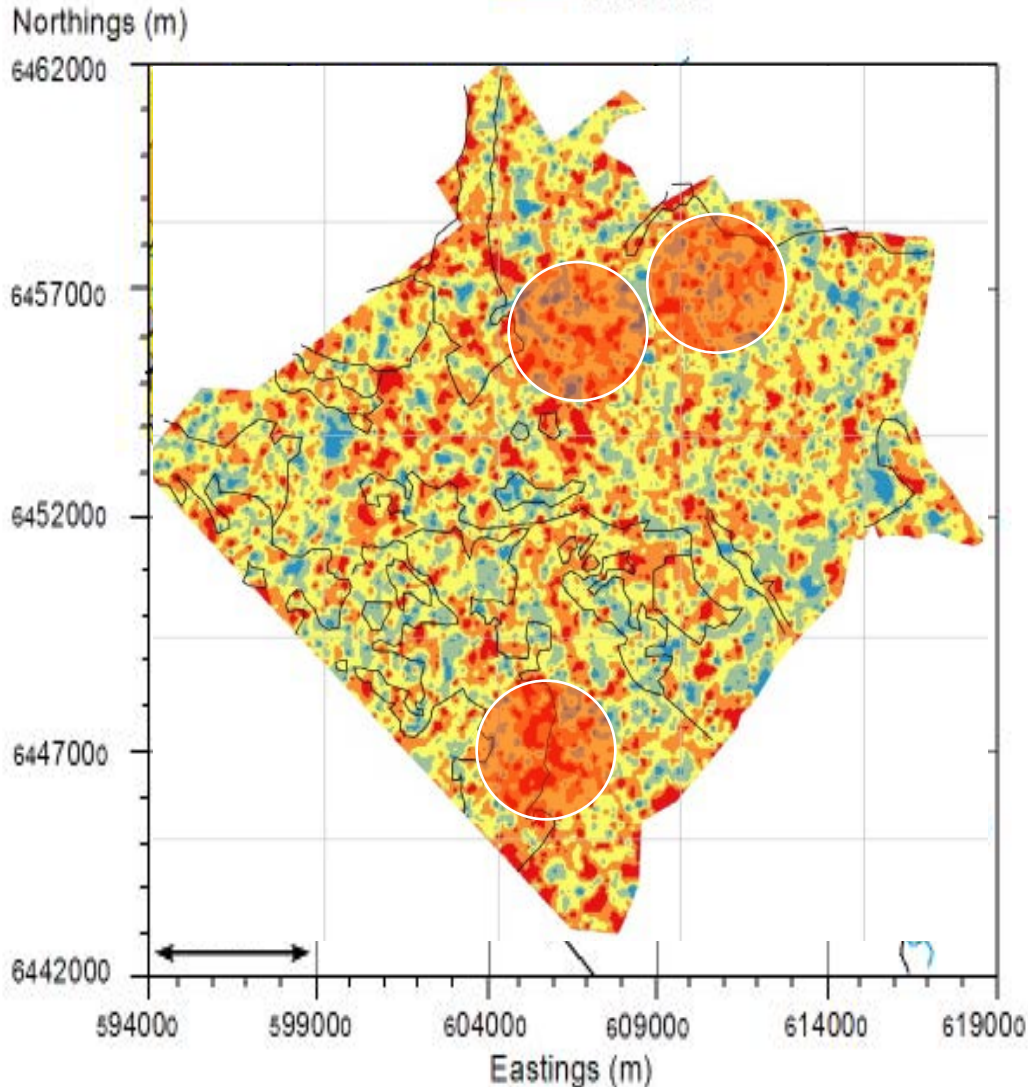
>



Input > Model

...because we estimated ancillary data
onto calibration points

Results and Discussion: Error



Combined

Influenced by;

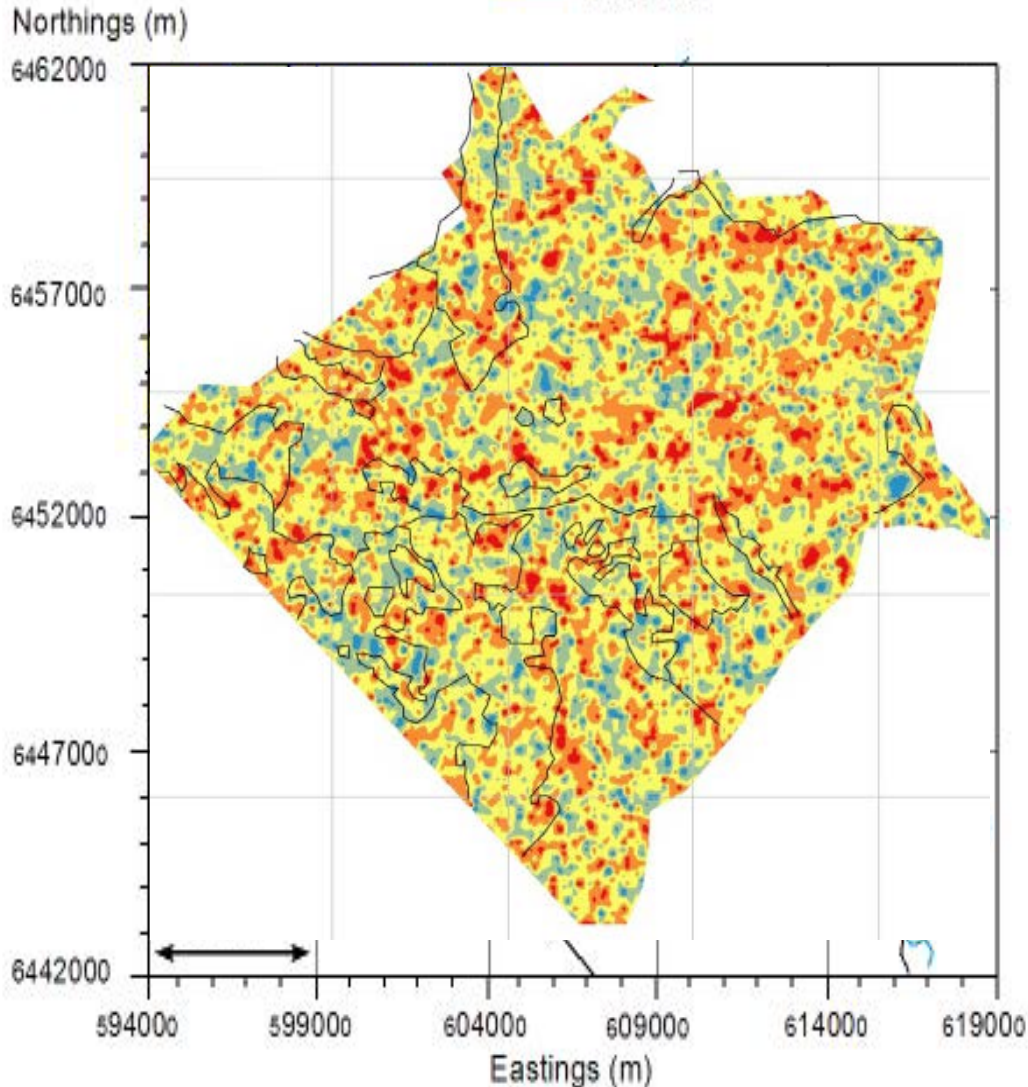
- i) Pedoderm boundaries, and
- ii) Ancillary data (???)

SD

(cmol(+)/kg)



Results and Discussion: Error



γ -ray

Influenced by;

i) Not really sure but if there is a psychologist in the room?

SD


($\text{cmol}(+)/\text{kg}$)

 < 9.0

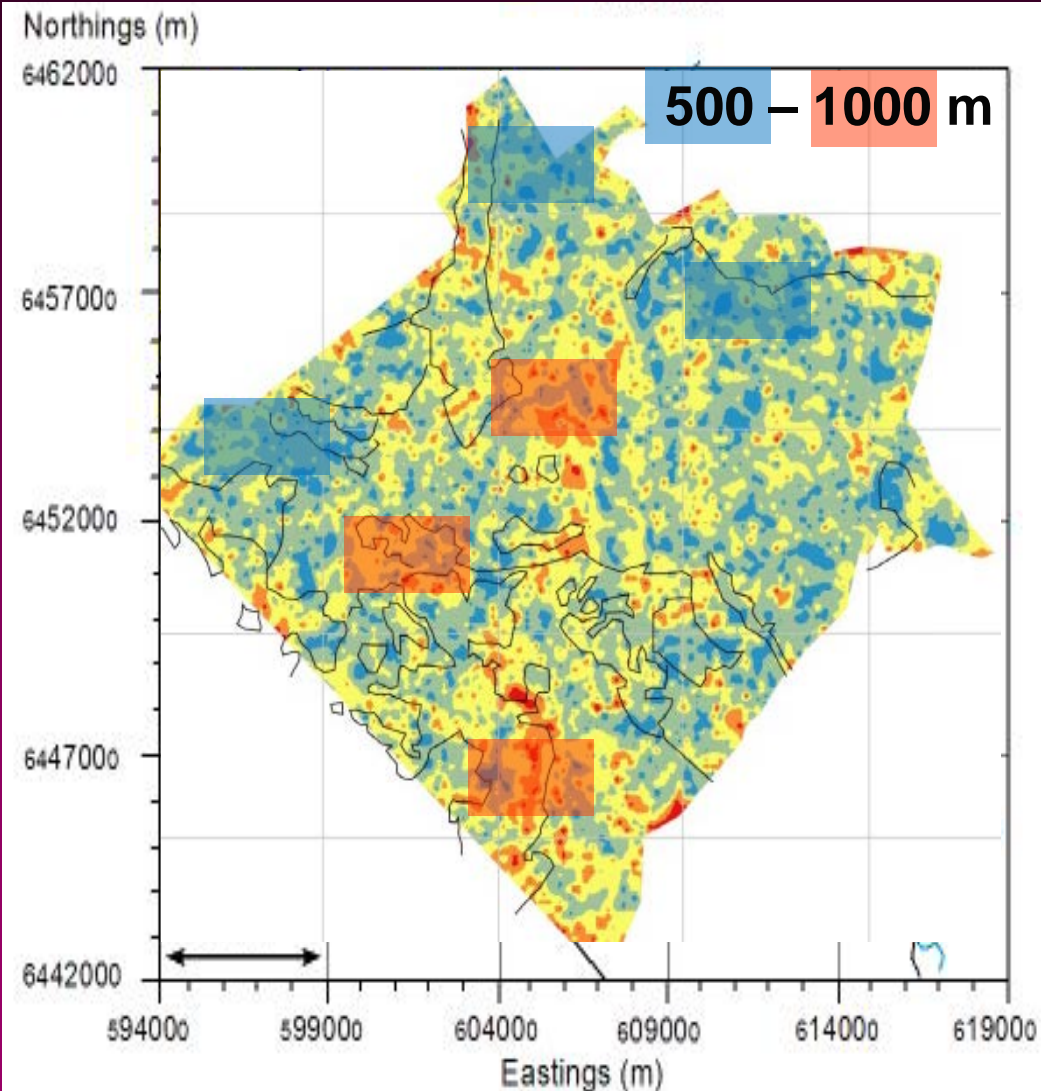
 < 9.4

 < 9.8

 < 10.2

 ≥ 10.2

Results and Discussion: Error



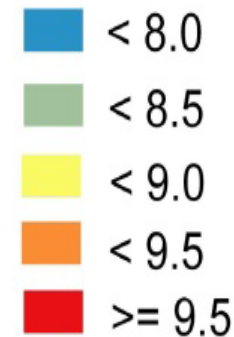
EM

Influenced by;

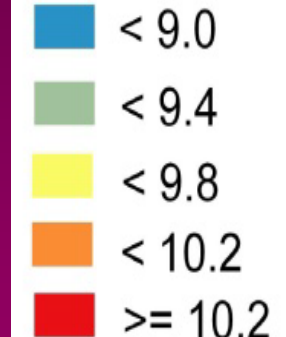
- i) Dryland and irrigated sampling density
- ii) Pedoderm boundaries

SD

(cmol(+)/kg)



(cmol(+)/kg)



<

EM < γ -ray

...because smaller nugget variance

Conclusions



Main

Combined error ~ 12.93 cmol(+)/kg is larger than observed CEC (6.8 cmol(+)/kg)

To reduce model error
applying some pre-processing techniques
to improve the data quality or to look use
other available ancillary data

To reduce input error
use smaller sampling interval and in
particular near the edges of the survey
extent and also at Pedoderm boundaries.

Jasper Johns

0 through 9 1961 Oil paint on canvas

Tate - Presented by the Friends of the Tate Gallery 1961



UNSW
AUSTRALIA

An error budget for mapping field-scale soil salinity at various depths using different sources of ancillary data

Huang, J., Barrett-Lennard, E., Kilminster, T.,
Sinott, A., Triantafilis, J.

Pedology

An Error Budget for Mapping Field-Scale Soil Salinity at Various Depths using Different Sources of Ancillary Data

To manage soil salinity, farmers need to map its variation, often quantified as the electrical conductivity of a saturated soil-paste extract (EC_e , $dS\ m^{-1}$). However, EC_e determination is time-consuming and expensive. Previous studies have evaluated the use of digital elevation models (DEMs, i.e., elevation), airborne γ -ray (γ -ray) spectrometry (i.e., K, U, and Th) and electromagnetic (EM, i.e., EM38 and EM34) data to map EC_e at the district scale. Herein we use similar ancillary data set and empirical best linear unbiased prediction (E-BLUP) to make maps of EC_e at different depth intervals (0–0.25, 0.25–0.50, and 0.50–0.75 m) at the field scale. The ancillary data was collected using a ground-based mobile sensing system which included; a GPS which provided spatial coordinates (Easting, Northing), a RS700 (γ -ray) mobile spectrometer, and a DUALEM-1. An error budget procedure was conducted to quantify the model, input, and individual covariate errors of EC_e . Results show that while none of the γ -ray data were significant, scaled Easting, elevation, and 1-m horizontal coplanar (1mHcon) were optimal for mapping EC_e at 0 to 0.25 m, while 1mHcon was optimal at 0.25 to 0.50 m and 0.50 to 0.75 m. Among all the individual covariate errors for mapping 0- to 0.25-m EC_e , elevation ($0.40\ dS\ m^{-1}$) was smallest, followed by 1mHcon ($2.23\ dS\ m^{-1}$). To reduce error, additional soil samples are necessary to prevent the edge effect of the kriging process. Additionally, inversion of EM data could be used to improve EC_e mapping considering the relatively large model error associated with EM data in the subsoil of inverted salinity profiles.

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Aidan Sinnott

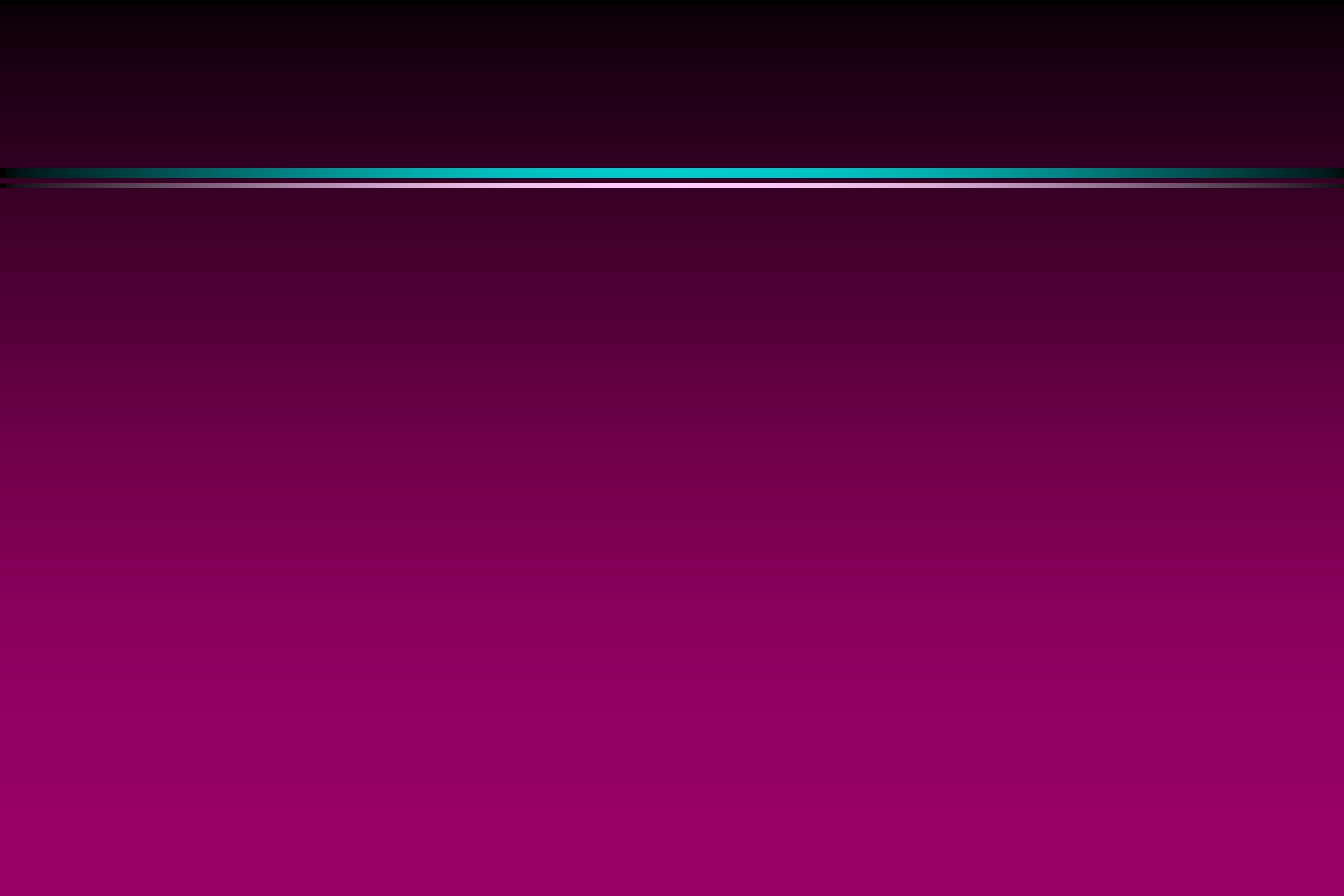
Precision Agronomics Australia
9 Currong St.
PO Box 2418
Esperance WA, 6450
Australia

John Triantafilis*

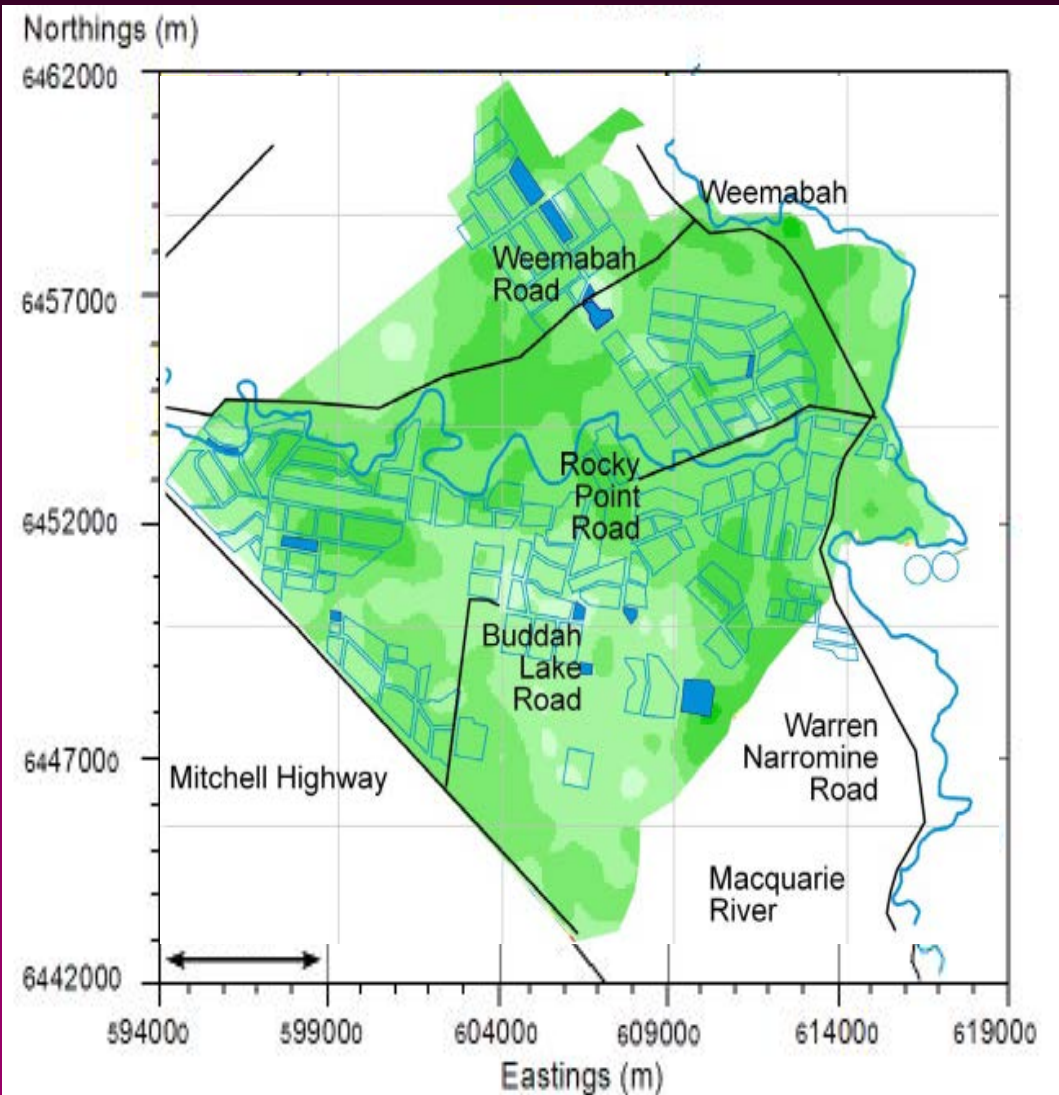
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Kensington NSW, 2052
Australia

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SOIL SCIENCE SOCIETY
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79, 1717-1728



Results and Discussion: Ancillary data



Gamma-ray spectrometry

0

Topsoil

0.35

Thorium

(ppm)



Results and Discussion

LMM models - variogram and goodness fit

<u>Variogram</u>	Spherical	Exponential	Model		Spherical	Exponential	
σ^2 (partial sill)	6.108	6.847	Pearson' r		0.656	0.653	
range	1.1	0.4	Lin's	Estimate	0.616	0.612	
			SSPE		Mean	1.007	1.007
nugget	21.88	21.17			Median	0.617	0.588
			ME (<u>cmol</u> (+)/kg)			0.011	0.011
Log-likelihood	-346.3	-346.7	RMSE (<u>cmol</u> (+)/kg)		5.129	5.152	

Introduction

*Irrigated
cotton
production*



Murray Darling Basin

Owing to the semi-arid climate, large areas extensively developed for irrigated agricultural production.

Whilst irrigation to Vertosols has brought prosperity, there have been some isolated environmental impacts.

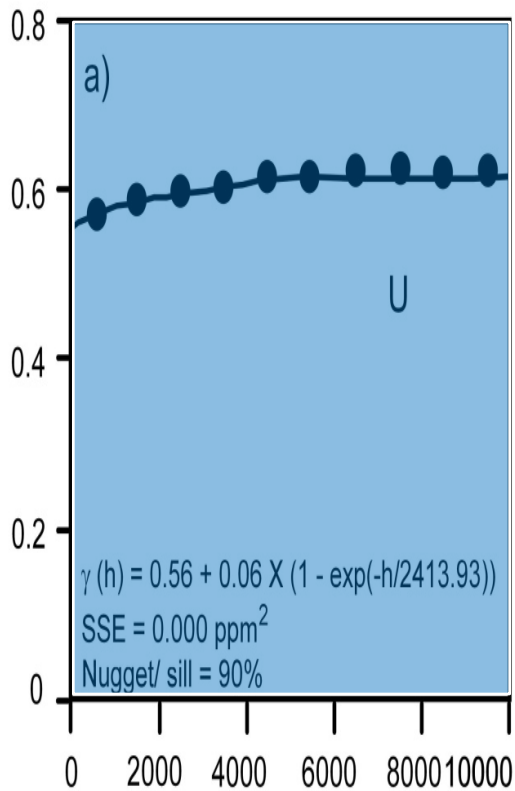
*Irrigated
rice
farming*



Results and Discussion

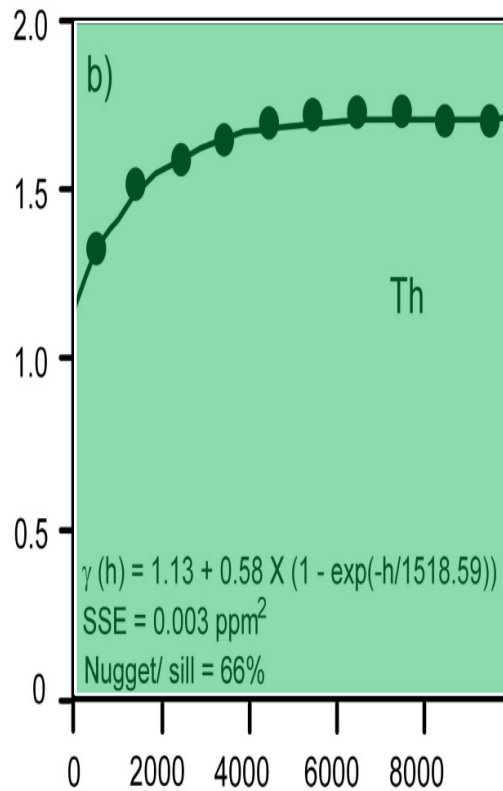
LMM models - variogram and goodness fit

Semivariance



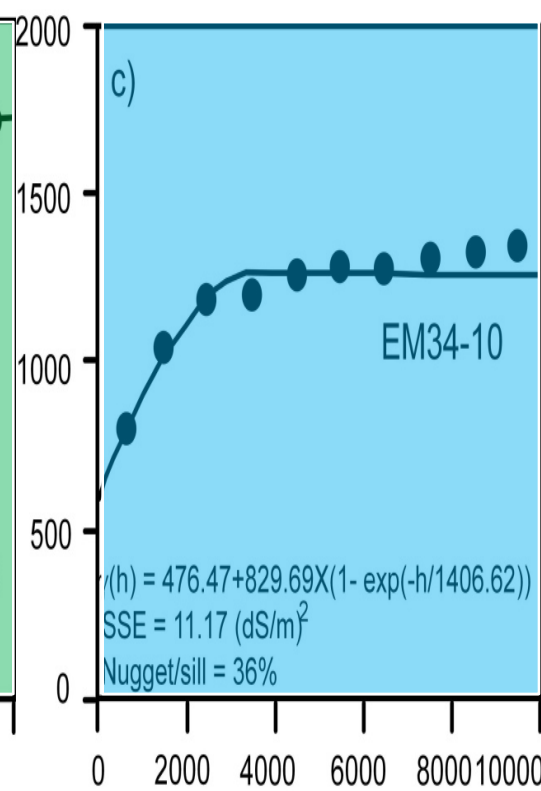
Lag distance (m)

Semivariance



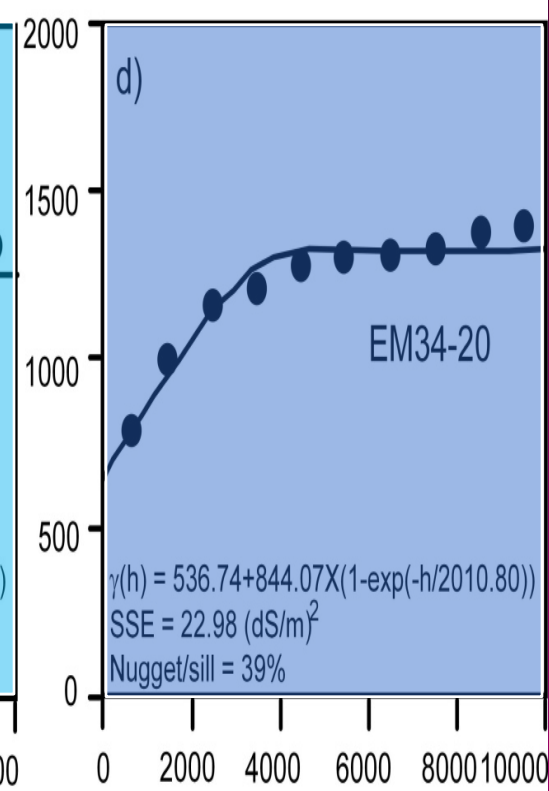
Lag distance (m)

Semivariance



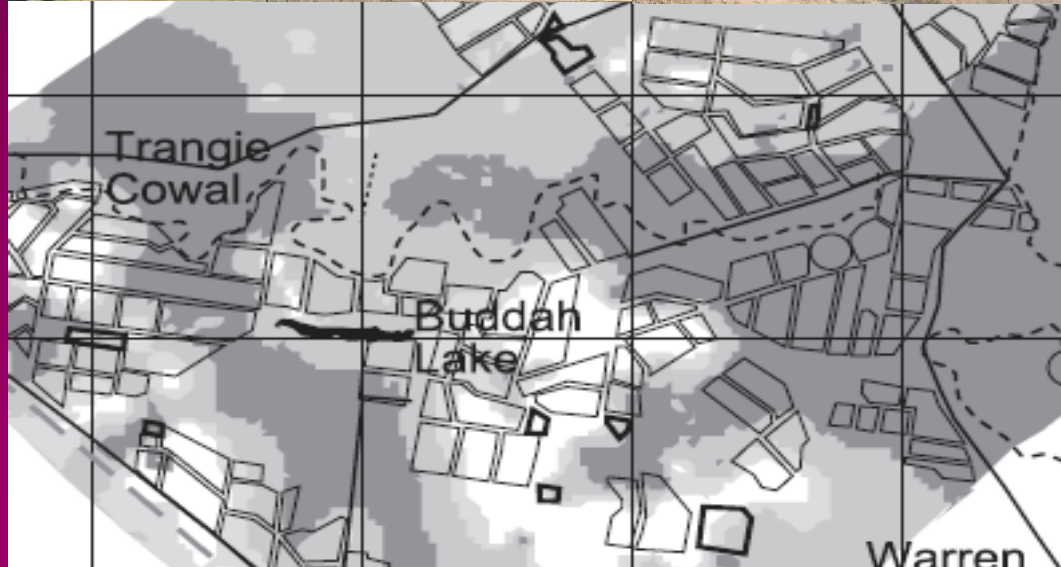
Lag distance (m)

Semivariance



Lag distance (m)

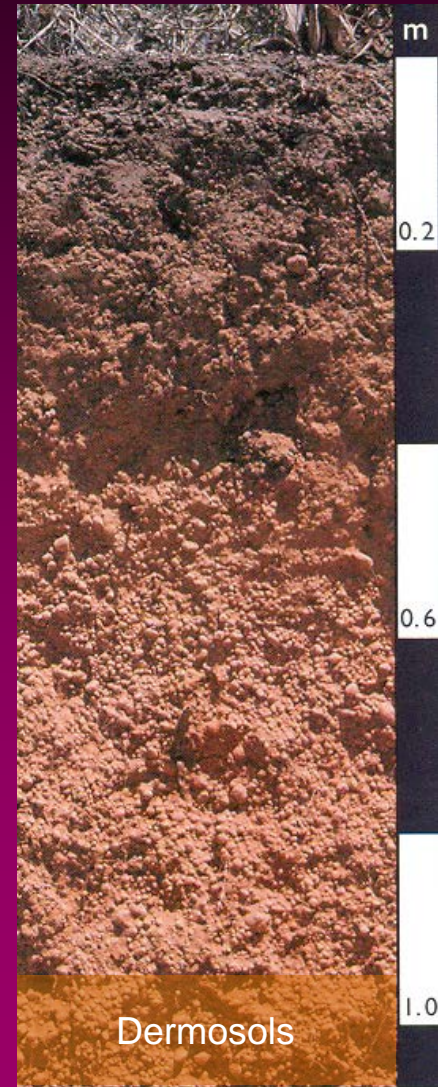
Introduction



Environmental impacts

One of these has been the creation of shallow saline water tables (e.g. Buchanan and Triantafilis, 2009).

One of the drivers has been susceptibility of landscape to deep drainage (Woodforth et al., 2012) via **prior stream channels (Dermosols)**.



Gamma-ray spectrometry

Application

Depth (m)

Remote (air-borne)

Topsoil

0
↕
0.4

Airborne

K
U
Th
TC

Mapping
clay content,
CEC,
mineralogy



EM instruments

Application

Root zone

Sub-soil

Mapping
clay content,
salinity, CEC
and moisture
status

Operating Frequency:
14kHz

Depth (m)

h v
0
0.75
1.5

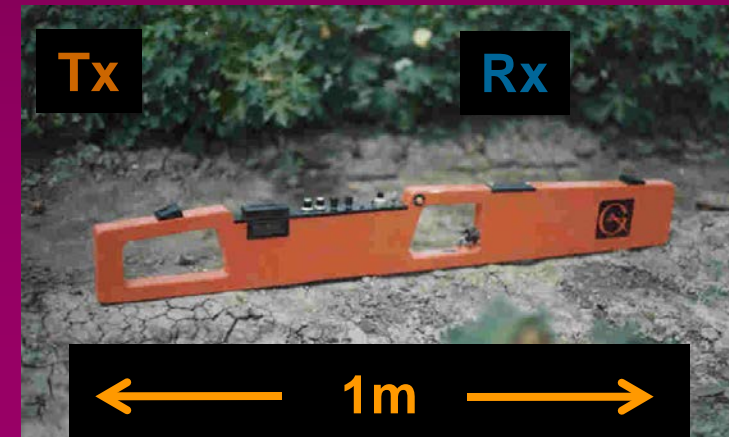


Proximal

Geonics EM38

EM38h

EM38v



EM instruments

Application

Depth (m)

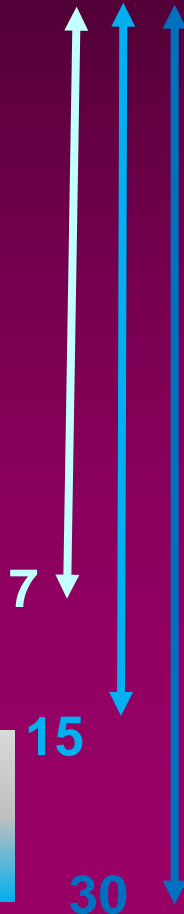
Proximal

Geonics EM34

Vadose zone

Shallow groundwater tables

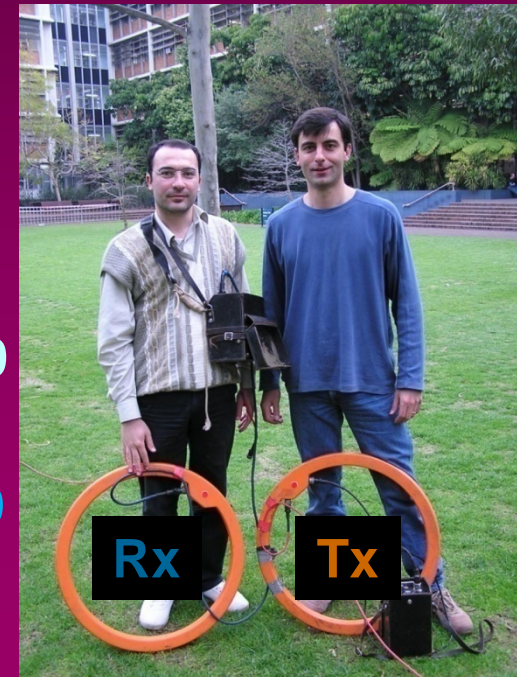
h
0



EM34-10

EM34-20

EM34-40



Operating Frequency:
6.4, 1.6 and 0.4 kHz